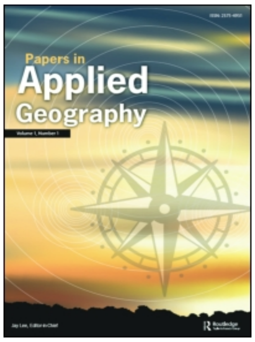

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APPLICATION ARTICLE

Spatial Cluster Analysis of High-Density Vehicle–Bear Collisions and Bridge Locations

Ray Eslinger and John Derek Morgan

Department of Earth and Environmental Sciences, University of West Florida, Pensacola, Florida

ABSTRACT
Florida's automobile transportation corridors have fragmented the natural range of Florida's black bear, greatly impacting its movement. This fragmentation limits black bear migration and genetic interchange and prevents them from utilizing seasonally important nutrients. In extreme cases, highways lead to vehicle–bear collisions as the animals attempt to cross the road. The Florida Fish and Wildlife Commission (FWC) has attempted to mitigate these negative factors with highway crossing structures. These structures are expensive, however, and limited funding reduces their feasibility as construction projects. This article presents the methods and results of a spatial cluster analysis of black bear road kills from 2011 to 2015, and relates these findings to existing bridge structures. The purpose of conducting this analysis is to assist the FWC in their analysis of optimal roadway crossing feature selection for potential conversion to overpass. The results of this analysis have the potential to inform an ongoing partnership effort between the FWC, the U.S. Fish and Wildlife Service, and the Florida Department of Transportation that seeks to use science-based data in selecting wildlife roadway crossing locations.

KEYWORDS
Florida black bears; Getis-Ord Gi*; kernel density estimation; spatial cluster analysis

Florida black bears (*Ursus americanus floridanus*) are currently estimated to have a population of more than 4,000. In the 1970s, the Florida black bear population had reached dangerously low levels with between 300 and 500 bears. To protect the few remaining bears, the Florida Fish and Wildlife Commission (FWC) instituted a hunting moratorium for specific geographic areas. This moratorium would eventually become statewide and helped the Florida black bear population rebound to about 3,500 in the early 2000s and an estimated 4,350 adult bears reported in March 2016 (STAATS 2016).

While the bear population was rebounding, the Florida human population was exploding, going from 9,746,324 in 1980 (Forstall 1995) to more than 20 million in 2015 (U.S. Census 2016). The growth of these two populations, bears and humans, has set a course for increasing interaction as activity spaces and habitats increasingly overlap. One place in particular that human–bear interaction is increasingly problematic has been on Florida's automobile transportation corridors (or roadways).

This article presents the methods and results of a spatial cluster analysis of black bear road kill from 2011 to 2015. The purpose of conducting this analysis is to assist the FWC in their analysis of optimal roadway crossing feature selection for potential conversion to overpass. The results of this analysis hold the potential to inform an ongoing partnership effort between the FWC, the U.S. Fish and

CONTACT Ray Eslinger ere3@students.uwf.edu College of Science and Engineering, University of West Florida, Pensacola, FL 32514.

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Wildlife Service (USFWS), and the Florida Department of Transportation (FDOT) that seeks to used science-based data in selecting wildlife roadway crossing locations

Background

Events such as crime, disease, and even vehicle–animal collisions occur in nuanced ways across space and time and are typically recorded at specific points. To develop practical information on the geographic clustering (loosely termed hot spots) and profile of these incidents within a given study, the ability to group events in clusters is helpful. A variety of techniques have evolved that can inform understanding of the spatial clustering of events based on point data (*e.g.*, local Moran's I and nearest neighbor analysis). Hart and Zandbergen (2014), in their article on crime hot spot methods, described these techniques as broadly categorized between those that are based on aggregated incident locations and those that perform an analysis of individual points. The two methods of hot spot analysis most relevant to the methods employed in our project are called *kernel density estimation* (*KDE*) and the *Getis-Ord Gi** statistic. The two methods are described here and given context within the project that motivated this article.

KDE falls into the analysis of point-patterns category of methods. KDE depends on the probability theory where the density of a continuous random variable is a function that describes the relative likelihood for this random variable to take on a given value (Silverman 2002). Within the context of hot spot mapping, we are trying to map the probability that specific incidents will occur at specific places (Eck *et al.* 2005). To do this, a kernel is passed over a grid overlain on the point (or line) data set that generalizes or "smooths" discrete data points. The resulting visualization surface is useful for data exploration, but limited with regard to statistical inference purposes.

The kernel itself can be naive (considering all points that fall within its bound the same) or use a geographic weighting scheme where it considers points toward the center with greater weight as described in O'Sullivan and Unwin (2003). The variable weighting approach to KDE has taken on a variety of different implementations but is usually informed by the approach taken by Silverman (1986) and later Bailey and Gatrell (1995) where they use a quartic kernel defined by:

$$k(u) = \begin{cases} \frac{3}{\pi}\ (1-u^T u)^2\ for\ u^T\ u \leq 1 \\ 0 \qquad\qquad\qquad otherwise \end{cases}$$

where u is the distance from the center of the kernel divided by the bandwidth, and superscript T indicates the transpose matrix. With this, $k(u)$ results in a bivariate probability density function, known as the *kernel*. After running this kernel over a given point pattern, a continuous surface is produced that can then be utilized for visual exploratory purposes, such as the identification of cluster areas.

The Getis-Ord Gi* statistic falls into the aggregated incident category of methods. Let us expand on the distinction between these two commonly used hot spot methods as their differences are relevant to our project methodology and results. A simple example of the formula used to obtain the Getis-Ord Gi* statistic is described in O'Sullivan and Unwin (2003) as:

$$G_i^* = \frac{\sum_j w_{ij}(d)x_j}{\sum_{j=1}^n x_j}$$

where $w_{ij}(d)$ are weights from a spatial weights matrix and x_j denotes attribute values at locations j. Spatial dependence then is taken from the results of G_i, which is a proportion of the sum of all x values in the study area accounted for by just the neighbors of i.

When looking specifically at the occurrences of incidents (*e.g.*, bear–vehicle collisions) and not attributes associated with them (*e.g.*, age of bears), an aggregated count method is used for x_j. For instance, incidents might be collapsed into a single point that meets a nearness threshold, resulting in a count value that will be used for x_j. A particular benefit of using the Getis-Ord Gi* statistic approach to hot spot analysis is that the resulting values give a measure of statistical significance. For this reason, the Getis-Ord Gi* statistic has become the preferred method in regional hot spot mapping and analysis.

Hot spot methods such as KDE and the Getis-Ord Gi* statistic have been used by a number of researchers within the context of analyzing wildlife activities and patterns relevant to this article. Clevenger, Chruszcz, and Gunson (2003) examined the spatial patterns and factors influencing small terrestrial vertebrate road-kill aggregations in the Bow River Valley of Alberta, Canada. In their study they surveyed roads varying in traffic volume, configuration, and adjacent landscape attributes for road kills between 1997 and 2000. To perform their analysis they used a method called Ripley's K, which produces an index that helps determine if distances between points and their nearest neighbors are closer together than would be expected by random chance (Levine 2004). Although Clevenger, Chruszcz, and Gunson (2003) did not use KDE or the Getis-Ord Gi*, their findings that proximity to safe passage (drainage culvert or wildlife crossing structure) below roads in our study area was positively correlated with snowshoe hare and mammal road kills are very relevant to the scope of our project.

Ramp *et al.* (2005; Ramp, Wilson, and Croft 2006) used kernel estimation methods to model wildlife fatality hot spots along roads in Australia for a variety of species ranging from grey kangaroos to swamp wallabies. In their 2005 study they identified hot spots using a probability method that considered incident points in relation to an assigned point every 10 m along a road network. A year later, in Ramp, Wilson, and Croft (2006), they produced a similar study that focused on prediction by including in their analysis variables such as elevation, tree canopy cover, and recommended speed limit. The purpose of this study was to see how small-scale features of roadside habitat influence the probability of fatalities. They concluded with a few important findings, such as tall roadside vegetation reducing collision frequency, specifically for bird species.

A number of recent studies have used spatial autocorrelation to examine vehicle crash spots. Truong and Somenahalli (2011) used Getis-Ord Gi to identify pedestrian–vehicle crash hot spots and identify unsafe bus stops. Nie *et al.* (2015) used network-constrained KDE and network-constrained Getis-Ord Gi to detect spatial clusters and identify dangerous road segments. Kuo, Zeng, and Lord (2011) compared Moran's I, Getis-Ord Gi, and KDE and developed strategies for the appropriate tool to identify hot spots consistent with the data's characteristics and the study's objectives.

Specific to studies of bear populations, Wooding and Brady (1987) showed that bears lose 2.47 acres of habitat for each kilometer of highway. Kasworm and Manley (1990) showed that noise from highways leads to bears avoiding road adjacent habitat. Range fragmentation caused by highways intersecting the bears' habitat causes changes to the size of the bears' range and distribution. These range and distribution changes were documented by Brody and Pelton (1989) and Proctor *et al.* (2002). Brandenburg (1996) showed that highways alter the bears' movements and prevents the bears from using seasonally important nutrients. Dixon (2004) demonstrated that range fragmentation has been an obstacle to migration and genetic interchange between the bear subpopulations.

Pienaar, Telesco, and Barrett (2015) showed mitigation techniques can be successful in altering individuals' attitudes when the FWC makes use of public outreach efforts. Pienaar, Telesco, and Barrett also showed that people tend to fall back to hunting and trapping as a mitigation technique without public education and outreach. McCown *et al.* (2004) showed there have been many mitigation systems designed to alter animal or human behavior. These devices use motion sensing to either flash lights to warn motorists or turn on lights and noises to scare animals. McCown *et al.* discussed that these techniques have limited efficacy because drivers ignore the flashing lights and animals become accustomed to the lights and noises. McCown *et al.* went on to demonstrate that wildlife underpasses and overpasses are effective but costly collision mitigation techniques. Clevenger *et al.* (2003) demonstrated that a wildlife overpass in Alberta, Canada, is routinely used by black bears. Foster and Humphrey (1995) showed that wildlife crossing structures have been highly successful for panthers when coupled with extensive habitat movement studies, which Roof and Wooding (1996) later confirmed with bears in their work.

Method

This project examines several pieces of data acquired primarily from the FWC and FDOT. These data include the current range of the Florida black bear as well as spatial data showing the location of bear road kills. The bears' home range is an area that is inhabited in search of food and water. This shapefile contains rare, occasional, common, and abundant ranges of the Florida black bear as reported by the FWC. The FWC continually records human–bear interactions such as collisions so that this information can be used for long-term road improvement planning (FDOT 2016). The FWC maintains records of bear road kills where a geographic coordinate can be obtained. These data are recorded when the road kill is reported and the carcass is collected. Because the FWC is looking for a hot spot analysis of the most current data, this project looked at road kill data collected between 2011 and 2015. These data are also overlain with statewide FDOT bridge and overpass data. The FDOT continually updates its bridge and overpass shapefiles and publishes the data quarterly.

To more closely capture the way in which human–bear interaction has and is occurring, popular commuting transportation corridors (humans moving through habitat) will be of particular focus in the analysis. A precedent for this approach can be seen in the work of Pienaar Telesco, and Barrett (2015), who examined the specific methods for managing human–bear conflict within Florida by looking at how human activities influenced human–bear interactions. Both FWC data sets were updated in January 2016 to include the full year's data for 2015. Road and bridge data were downloaded from the FDOT FTP site. Both FDOT data sets were updated on 12 March 2016. In 2012, the FWC divided the state into seven bear management units (BMUs). The BMU is a defined area within which the FWC can work with the community to more effectively manage the Florida black bear. These BMUs contain each of the seven bear subpopulations and by analyzing the data in each BMU and as a whole, the project can better identify the statistically significant hot spots.

To determine the location of bridges the state of Florida can use as wildlife underpasses, we had to examine the bear road kill data to look for patterns that can be identified as hot spots in comparison to the transportation infrastructure data. Specifically, we looked for clusters of bear road kills that signify something out of the ordinary from the rest of the data. There are several methods to perform this type of analysis such as kernel density analysis, the global Moran's I test and the Getis-Ord Gi* test. This project used KDE to analyze the data statewide, but utilized the Getis-Ord Gi* method to examine the data on a local level. Kernel density analysis is useful for showing where points are concentrated, and estimates the values at unsampled locations based on its neighbors. This continuous surface smoothing creates an estimated surface based on distribution and density (Chainey and Cameron 2010). This estimation makes the analysis visually identifiable. Although a kernel density analysis does not require an aggregated population field, this project used one to maintain consistency with the Getis-Ord Gi* method, which does.

We used the Integrate and Collect Events tools to snap features within a specified distance of each other together. This created a new layer containing the points at each unique location with the associated count to indicate the number of incidents. The specified distance although subjective, was chosen based on knowledge of the data. If this were 911 data, then each point within 50 feet of each other could be considered the same address. Because many road kills are happening on the same 5- and 6-mile (8,047 m–9,656 m) sections of road, we used a distance of 9,000 m. In other words, all incidents within 9,000 m of each other were considered to have happened at the same location. Because the Integrate tool modifies the input data by changing locations, this project used the Copy Features tool to preserve the original data.

Running the Integrate and Collect Events tools within ArcGIS (version 10.4, 2017, Esri) generates a layer with graduated circles reflecting the number of points at each location. More important, the Integrate and Collect Events tools generated an ICOUNT field in the attribute table. This is the population field used to run the Kernel Density tool in ESRI's ArcGIS. The output cell size of 2,172 m was the default value.

The Kernel Density tool in ESRI's ArcGIS identified major hot spots in the Central and East Panhandle sections and minor hot spots in every remaining area of Florida with the exception of the

Big Bend area. Although it produces a visually identifiable map, Kernel Density does not produce markers of statistical significance such as *z* scores and *p* values (Ord and Getis 1992, 2001), so this project ran the Getis-Ord Gi* analysis to confirm the results of the kernel density analysis at a local level.

Hot spot analysis identifies areas with significant spatial clusters of high values and low values (Grubesic and Murray 2001). The Getis-Ord Gi* analysis generates *z* scores and *p* values that are measures of statistical significance. These statistical measures are useful in determining whether clusters of data are more pronounced than in a random sampling (Ord and Getis 1995).

Projects in which data need to be tested for statistical significance on a subregional or local level require a statistics tool to test each feature in context with its neighbors, such as the Getis-Ord Gi* statistic as originally described by Ord and Getis (1992, 1995). Whereas the kernel density function does a simple density calculation based on the user-specified radius and raster cell size, the Getis-Ord Gi* statistic works by looking at the value of each feature in a data set in the context of its neighbors' values. For this project the data were broken down into BMUs and examined on a local level.

When running the *Getis-Ord Gi** tool in ArcGIS there are two inputs that will call on the user's familiarity with the data. The first input to consider is choosing the correct conceptualization of spatial relationships (CSR). The CSR suggests that there is a relationship between aggregated input field values and the spatial location. For example, a busy highway with a curve that obscures visibility might generate numerous bear–vehicle collisions. For our project we used inverse distance as the CSR following Manepalli, Bham, and Kandada (2011), who showed inverse distance to be an appropriate CSR to use in demonstrating relationships between roadway design and the likelihood of accidents.

Everything in the inverse distance band will be weighted and will exert influence on its neighbors. Features outside the critical distance are ignored. Ignoring these features recognizes that the relationship between features diminishes with distance. This concept recognizes Tobler's (1970, 236) now widely accepted First Law of Geography, which states "everything is related to everything else, but near things are more related than distant things." Following McCown *et al.* (2004), we used 5,400 m, the range radius of an adult black bear, as our critical distance.

Running the *Hot spot Analysis (Getis-Ord Gi*)* tool creates a new data set with the high values colored red to signify hot spots, low values are colored blue, and areas with no statistical significance colored yellow (Figure 1). In other words, high-value areas surrounded by other high-value areas are shaded red.

Results

Based on our discussion with officials at the FWC and review of their previous work in this area, wildlife roadway crossing structures are a key part of their strategy in bear management (FWC 2012). They reported that wildlife crossing structures have proven very effective in reducing wildlife–vehicle collisions. McCollister and Van Manen (2010) found underpasses reduced vehicle-related wildlife mortalities by 58 percent along a recently upgraded section of U.S. Highway 64 in North Carolina.

Running the *Kernel Density* tool on our bear road kill data we identified clusters in the East Panhandle, North, Central, and South BMUs (Figure 2) and the *Getis-Ord Gi** confirmed these results with a 90 percent or greater confidence level. We then overlaid the road and bridge data acquired from the FDOT and selected bridges in the identified hot spots and exported them to a separate feature set. We then added the latitude, and longitude, county, zip code, and BMU that each bridge was in. This process identified 376 bridges and overpasses in the selected areas and these data were exported to a table (Figure 3).

The range of the Florida black bear was overlain with the identified bridges. This confirmed the results of kernel density and Getis-Ord Gi* analysis, with the identified bridges located in the center of the bear ranges (Figure 4).

Simply identifying pattern clusters did not tell us unequivocally where our hot spots were. Rather an interpretation of the statistical results of Getis-Ord Gi* was informative to reject a hypothesis of spatial randomness. Specifically, calculating Getis-Ord Gi* for each feature in the bear road kill data set gave us resulting *z* scores and *p* values. The *p* value (a probability value) and the *z* score (standard

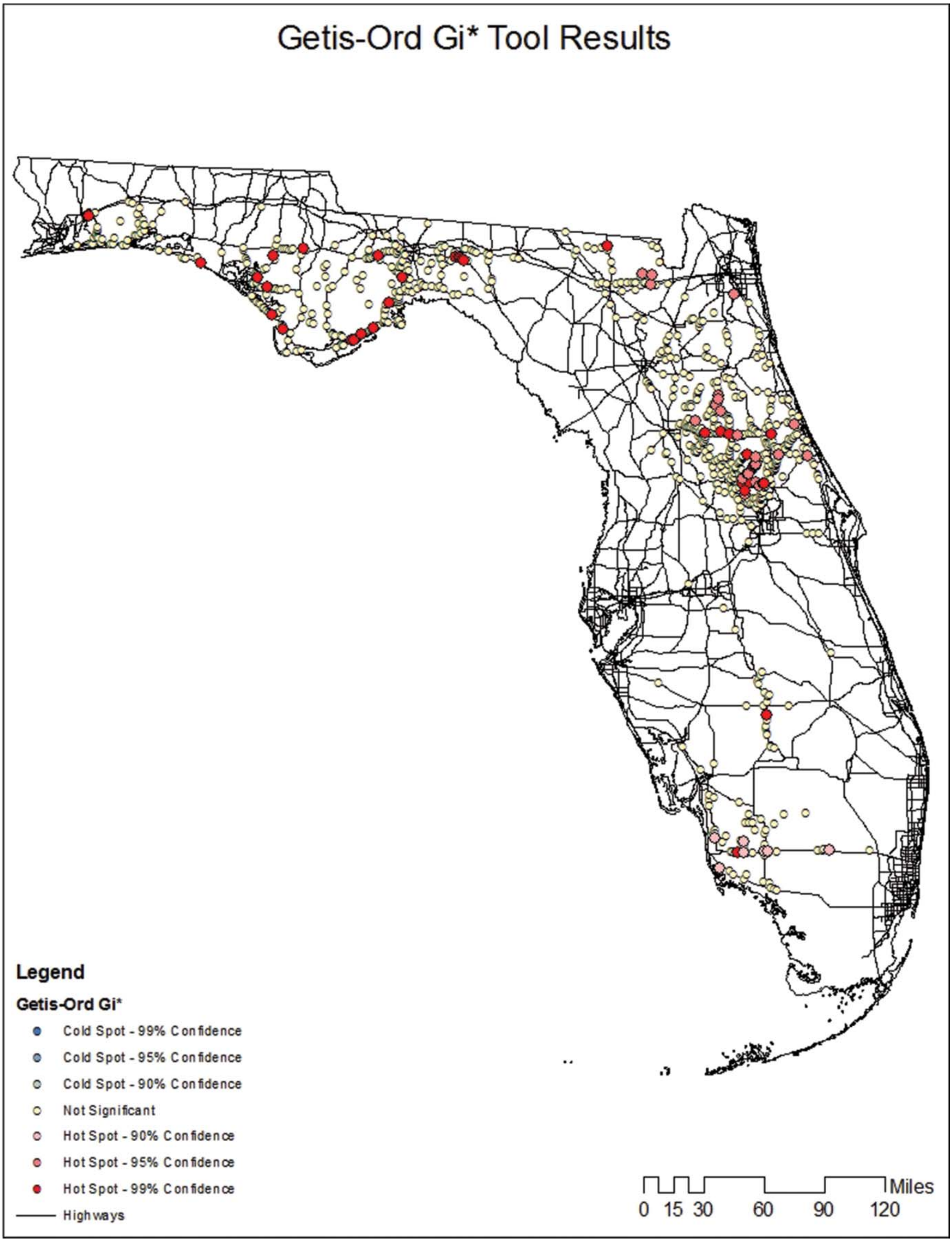

Figure 1. Getis-Ord Gi* tool results.

deviations) are associated with a standard normal distribution. By examining the resulting p values and z scores, we got a measure of how the observed spatial pattern compared to a theoretical random pattern.

We identified hot spots in every BMU except for the Big Bend area of Florida. The Big Bend area only had two road kills during the study period of 2011 through 2015, which was not enough to qualify

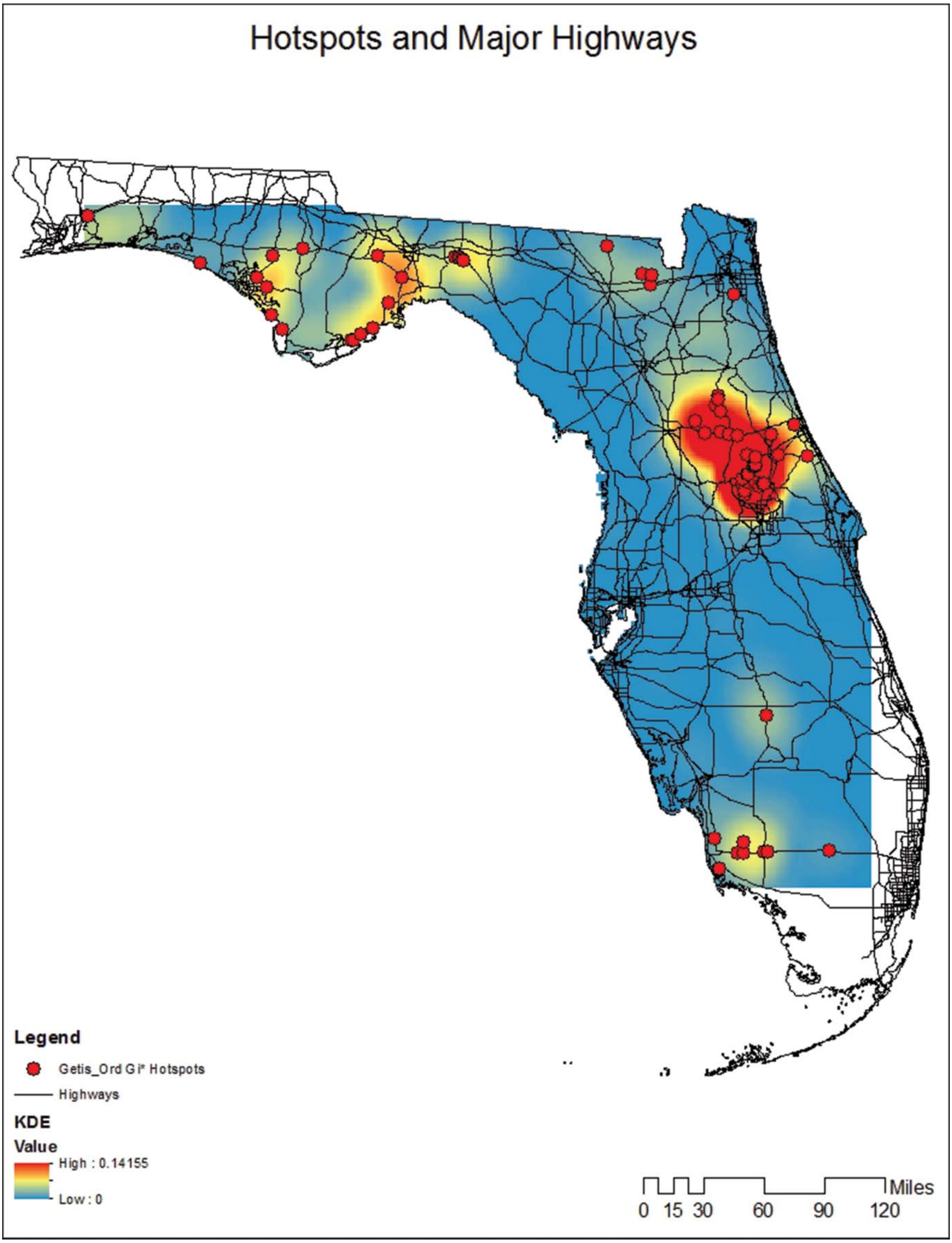

Figure 2. Hot spots and major highways. *Note*: KDE = kernel density estimate.

as a hot spot. The South Central BMU had one identified hot spot, and the West Panhandle had two isolated hot spots, which made it difficult to identify bridges for these areas. Using a search radius of 100 m as suggested by the FWC identified no bridges in these areas. The North BMU had a concentration of three, along with two isolated hot spots. The concentrated area was used to identify several

ST_NAME	L_POSTCODE	R_POSTCODE	PRIVATE	BRIDGE	FID_Bridge	County	BMU	POINT_X	POINT_Y
US-441	32778	32778	N	N	179	Lake	Central	-81.74203164	28.81090503
SR-46	32776	32776	N	N	194	Lake	Central	-81.49810743	28.81477049
SR-46	32771	32771	N	Y	181	Seminole	Central	-81.41956065	28.81517174
W SEMINOLE BLVD	32771	32771	N	N	396	Seminole	Central	-81.27743337	28.81606254
US-441	32778	32778	N	N	160	Lake	Central	-81.75981609	28.81518162
SR-19	32757	32757	N	N	173	Lake	Central	-81.68548023	28.82311398
ORANGE BLVD	32771	32771	N	N	238	Seminole	Central	-81.3379999	28.82845957
ORANGE BLVD	32771	32771	N	N	403	Seminole	Central	-81.32479927	28.8296055
	32771	32771	N	N	408	Seminole	Central	-81.32534761	28.83012101
I-4	32764	32764	N	Y	68	Volusia	Central	-81.3191087	28.8352132
US-17-92	32771	32771	N	Y	416	Seminole	Central	-81.32431681	28.83744536
CR-452	32726	32726	N	N	202	Lake	Central	-81.6898775	28.85154114
FORT FLORIDA RD	32713	32713	N	N	1	Volusia	Central	-81.32507273	28.85628792
FORT FLORIDA RD	32713	32713	N	N	2	Volusia	Central	-81.32545338	28.8562891

Figure 3. Sample from bridge identification table.

bridges that could be used as wildlife underpasses. Neither of the two isolated hot spots had a bridge within 100 m and thus produced no results.

The East Panhandle, North, Central, and South BMUs produced 376 bridges that could potentially be used as wildlife underpasses. All but one of these bridges was on public property. After identifying the bridges, we collected the location information to include the latitude and longitude, street name, zip code, county, and BMU. Given this information, the FWC can now work with FDOT and local county governments to select which of these bridges will best serve as wildlife underpasses and begin the planning process. The relatively high cost of using bridges as wildlife underpasses makes the planning process a long-term effort. Fortunately, FDOT has shown a willingness to work with the FWC in mitigating bear–vehicle collisions by placing bear crossing signs in high-collision areas. It is hoped that this cooperation will continue and FDOT will implement wildlife underpasses in future road improvement projects.

Conclusions

This project used two statistical techniques, KDE and Getis-Ord Gi*, to identify bear–vehicle collision hot spots, and then used these hot spots to identify bridges that could be used as wildlife underpasses. This article has shown that the combination of KDE and Getis-Ord Gi* provides meaningful and complementary results when attempting to identify clusters of hot spots with vehicle collisions. This is similar to the results from studies conducted by Manepalli, Bham, and Kandada (2011) and Flahaut *et al.* (2003), who used kernel density and spatial autocorrelation techniques such as Getis-Ord Gi* to identify hot spots of vehicle accidents in Belgium and Arkansas.

Limitations and future research

Although this project did not look at the factors that contributed to bear–vehicle collisions, it has been speculated that factors that limit visibility such as curves or small buffers between road and forest contribute to bear–vehicle collisions. This is an area of study that should be examined closely. McCown *et al.* (2004) showed in their studies that road design choices such as long, flat, straightaways coupled with cleared right of ways facilitate successful bear crossings. Some have suggested that seasonal causes might contribute to vehicle–bear collisions, and this would be another avenue for future research. If the FWC can identify the contributing factors in these hot spots, they can take these factors into consideration for future road improvement projects. This would save millions of dollars in property damage, as well as human and bear lives.

Another area of future study would be to couple this study with regional Global Positioning System (GPS) collar studies to identify areas where bears are crossing Florida's highways as McCown *et al.* (2004) did in the Ocala region in 2001, and again in 2004. Foster (1993) showed that wildlife crossing structures are highly successful when coupled with habitat movement studies. This was later confirmed

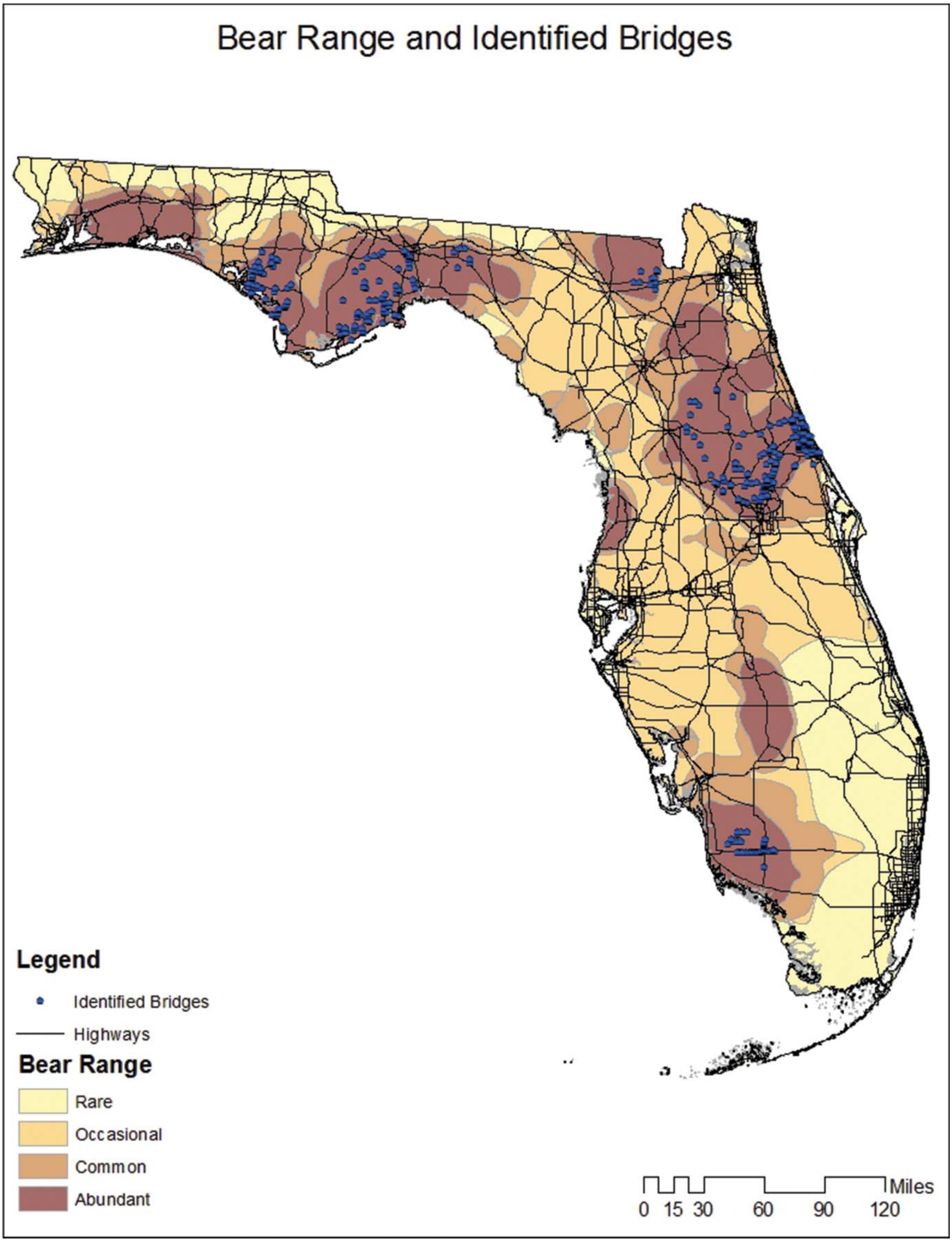

Figure 4. Bear range and identified bridges.

by Roof and Wooding (1996) in their work with bears. Similarly, Loraamm and Downs (2016) used a maximal covering location approach to identify the most effective fence coverage distance given a finite amount of wildlife crossing structures. They solved for four coverage distances using Florida panther telemetry tracking data, which captured frequent contact with roads. Results indicated that 2,000 m was the most effective coverage distance.

Finally, wildlife underpasses will help alleviate some of the negative impacts caused by highways fragmenting the Florida black bear's range. Brody and Pelton (1989) showed that highways intersecting bear habitat cause changes to the size of the bears' range and distribution. These findings were confirmed by Proctor *et al.* (2002). Brandenburg (1996) showed that highways alter the bears' movements and prevent bears from using seasonal nutrients. Dixon (2004) demonstrated that range fragmentation limits migration and genetic interchange between the bear subpopulations. Strategically placed wildlife underpasses will not only lessen bear–vehicle collisions, but they will also encourage bear migration, which would be especially beneficial in areas of low bear populations.

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